Preparing for Future Learning with a Tangible User Interface: The Case of Neuroscience

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Abstract—In this paper, we describe the development and evaluation of a microworld-based learning environment for neuroscience. Our system, BrainExplorer, allows students to discover the way neural pathways work by interacting with a tangible user interface. By severing and reconfiguring connections, users can observe how the visual field is impaired and, thus, actively learn from their exploration. An ecological evaluation of BrainExplorer revealed that 1) students who engaged in the open-ended exploration outperformed students who used traditional textbook materials and 2) correctly sequencing activities is fundamental for improving student performance. Participants who used the tabletop first and then studied a text significantly outperformed participants who read a text first and then used the tabletop. Additionally, those results were best predicted by the quality of students' verbalizations while using BrainExplorer. The implications of this study for preparing students for future learning with Tangible User Interfaces are discussed.

Index Terms—Computer-assisted instruction, education, input devices and strategies

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1 INTRODUCTION

TECHNOLOGY has revolutionized the field of neuroscience.[1] Over the last decade, neuroscientists have learned more about the brain than in the whole of the 20th century. State-of-the-art fMRIs have become widely available and allow researchers to track the smallest change in the activity of the brain. As more data become available and theories become more complex, neuroscience faces the challenges of systematizing that knowledge and translating scientific findings into easily understandable results for the general public and students. The brain is a dynamic organism, and its organization is not only tridimensional, but the connections between its parts are complex, and much of it is understood using computational models rather than traditional "paper" representations [42]. We consider neuroscience to be an example of a field of knowledge that will be increasingly taught in colleges and, possibly, K-12 education, as science ventures into new fields such as genomics, nanotechnology, advanced materials, cellular biology, and climate science. Many of these new content areas share with neuroscience the difficulties of systematizing, representing, and teaching their content to students using traditional media and methods, such as textbooks and tell-and-practice pedagogies. Educational neuroscience, thus, bears the difficult task of initiating novices into a highly complex field of knowledge. This task will be increasingly important for educators in the years to come.

The aim of this paper is to contribute to the research on and the design of new interfaces targeted toward complex, novel, college-level content areas in which traditional representations might be insufficient. Thus, our goal is to provide preliminary answers to two questions. First, why do students find learning about the brain to be such a challenging, effortful, and laborious task? Even medical students rank neurology as the most difficult medical discipline [33]. Obviously the brain's complexity makes it difficult to visualize neural pathways and grasp basic neuroscience concepts, but this is only part of the answer. Based on interviews with students in neuroscience, we observed that traditional instruction heavily relies on textual and static two-dimensional representations of the brain, organized into lists of concepts and ideas for students to learn. Indeed, a common curriculum design strategy in many fields of higher education is to organize detailed lists of content items and go through the list in a linear fashion. In previous work [3], we have suggested that the "list" design principle is not a good fit for disciplines that heavily rely on the understanding of the principles of complex systems. In the case of neuroscience, we suggest that lists, taxonomies, and two-dimensional static diagrams are not a good fit for the content taught. The brain is a highly spatial, dynamic, nonlinear, and interconnected structure and, thus, requires educational material tailored toward its unique features.

This hypothesis laid the foundation for the creation of the learning environment described in this paper. Inspired by related work aimed at improving science education, we designed a hands-on activity in which users can manipulate a to-scale replica of the brain that is overlaid with dynamic information using augmented reality techniques. Additionally, we heavily draw on the tradition of computational microworlds, wherein designers create environments in which student-driven experiments can take place by programming or assigning rules to virtual objects [10].

Additionally, we were interested in a more specific question: Given the characteristics of the content taught, what is the best way to introduce novices to the study of the brain? This question is an important one because the first contact with a domain lays the foundation for subsequent learning. Inadequate instruction causes erroneous interpretations and misconceptions, which can be

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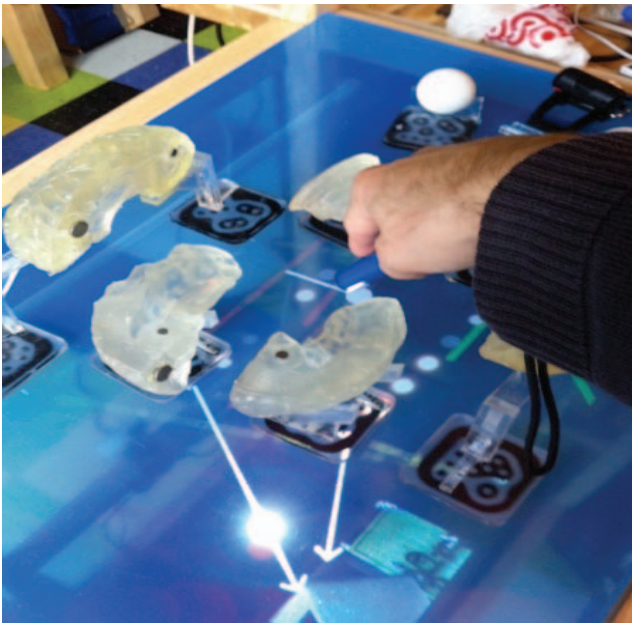
Fig. 1. A user cutting a connection between the lateral geniculate nucleus (LGN) and the visual cortex (V1).

deeply seated and resistant to change [38]. To guide our investigation, we based our design on the Preparing for Future Learning (PFL) framework [5]. More specifically, we explored how learning from manipulating digitally augmented physical objects impacts the foundations of users' knowledge in neuroscience.

The other contribution of this paper is to provide a description of an affordable, easy-to-use, and educationally relevant learning environment. Due to its low cost, BrainExplorer (Fig. 1) can easily be replicated and implemented in classrooms. Commercially available, proprietary solutions, such as the Microsoft Surface, cost far more than what most schools can afford and require a significant programming effort to build educational activities. BrainExplorer, instead, is organized in a modular way and allows users to quickly develop additional learning scenarios using free tools such as the open source Processing programming language [28]. Part of our goal is to create low-cost, easy-to-scale educational platforms based on open source, free software and off-the-shelf building blocks such as web cameras and infrared pens so that our system can be easily and cheaply deployed in classrooms. We build on many successful attempts at disseminating technologies to classrooms, such as Lilypads [7], Arduinos, GoGo Boards [37], and other robotics toolkits.

The paper is organized as follows: The next section describes the way brain concepts are currently taught and recent efforts in improving neuroscience education. We then describe our theoretical framework for designing learning activities. Next, we review related work, such as existing tabletops used for science education. We then introduce BrainExplorer, a tangible interface [16] exploiting technological developments such as low-cost infrared cameras and object tracking. Finally, we describe our empirical study and discuss the results of our evaluation in terms of classroom learning and the design of tangible educational interfaces.

2 THEORETICAL BACKGROUND

2.1 Current Instruction in Neuroscience

Most college-level neuroscience instruction still relies on traditional lectures and textbooks. The study of the brain is considered to be the domain of advanced undergraduates and graduate students for several reasons. First, much technical language is involved in the identification of different brain regions. Second, high-level spatial skills are required to visualize the relationships between these brain regions. It seems that the content of neuroscience is a typical case in which the difficulties in representing the information with traditional, static, two-dimensional media poses an extra burden on learners and that computational media offer a significantly different representational form [42]. Third, the brain is a complex system in which there are multiple possibilities for interconnections among its different parts, and each possibility has different consequences. In previous research [3], we have shown that traditional approaches to learning about complex systems are problematic because students focus on the memorization of several surface features of the domain instead of on the generative principles and behaviors behind it. Our system addresses these challenges by representing each brain region with three-dimensional tangibles, allowing users to associate a technical term with a physical object rather than an abstract idea and explore the multiple possible connections between these parts and the resulting behavior. Spatial relationships are readily deduced from these tangibles, which fit together to recreate the whole brain. The final challenge to making neuroscience more approachable is that the study of the brain is an extremely interdisciplinary field, requiring knowledge of basic biology, psychology, electrical circuits, and chemistry. Digitally augmented tangible interfaces can address this problem by making this complexity more accessible and visible (e.g., by focusing on a single concept at a time) and by making explicit and bringing to the fore the role of the interconnections in the brain. In the case of BrainExplorer, we chose to focus on a specific neural circuit involved in human vision.

In recent decades, several significant efforts have pioneered improvements in neuroscience education. These attempts fall into two categories: Those that utilize computer-based simulations and presentations and those that make use of actual physical manipulables in interactive classroom environments. In the first category, Brann and Slope [4] designed a new graduate neuroscience curriculum using WebCT to organize lectures and Power-Point presentations and Tegrity, an audiovisual recording system that was especially popular with students due to its note-taking capabilities. The authors emphasized the difficulties of teaching such a multidisciplinary domain, in which students need strong knowledge and skills in biology, chemistry, physics, and cognitive neuroscience. Their contribution was showing how new technologies (i.e., computer-based teaching tools) can address such complex teaching requirements. Av-Ron et al. [2] created a series of interactive computer models with simple user interfaces. Those applications allow college students to explore and manipulate different variables to learn about the electrical properties of individual neurons and the nonlinear behavior of neural networks. Unfortunately, no user study was presented, but those simple computer

simulations are both interesting and promising for engaging students with complex concepts in neuroscience. A major contribution was their proposal of simple yet effective design choices for creating computer simulations. Miller et al. [21] built an online interactive neuroscience adventure in which middle school students play the role of investigators exploring the effects of an unknown drug on the brain. This effort illustrates the benefit of coupling problem-based learning in neuroscience with technological solutions, such as online interactive learning environments. A significant difference between the pre- and posttests showed that this intervention helped students learn more about basic neuroscience concepts. The absence of a control group control, however, mitigates the implications of those results. In terms of using physical manipulables in the classroom, Keen-Rhinehart et al. [19] showed that using interactive methods for teaching action potentials was better than using traditional lectures. Students were instructed to use manipulables such as dried beans to simulate ions, and they had to move them across a picture of a neural cell membrane to describe the different phases of the action potential. They found that students working with the manipulables significantly outperformed peers who received only a standard lecture. In another effort, the success of the Brains Rule! Neuroscience Expositions program [44] suggests that interactive teaching methods can make neuroscience accessible to students as young as sixth graders. This program recruits neuroscience professionals to design interactive exhibits about different topics in neuroscience. For example, some recent exhibits have included "Modeling Neurotransmitters," in which kids use items such as playdough, candies, and pipe cleaners to model the actions of synaptic vesicles, neurotransmitters, and receptors and the "Mind and Muscle Maze," where children walk along a path, picking up puzzle pieces that illustrate the parts of the body that a developing nerve follows on its way to the hand [44].

To our knowledge, however, none of this work used tangible user interface technologies or conducted rigorous comparative learning studies. When designing Brain-Explorer, we took advantage of the pioneering work that has been done to ground our reflections on neuroscience education. More specifically, we tried to incorporate the engaging aspects of Miller's learning activity [21], in which adolescents learn concepts in neuroscience through an online inquiry-based adventure, and the hands-on components of Keen-Rhinehart's project [19], in which manipulables are used to describe action potentials.

2.2 Pedagogical Framework: PFL

Our design process relied heavily on the theory and findings of the PFL framework [5]. Here, we review the theory behind this framework and discuss studies supporting this approach. Finally, we discuss how the PFL framework informed the design of our learning activity.

2.2.1 Creating a Time for Telling

A constructivist approach to learning proposes that students make sense of new information by using and building upon prior knowledge. However, learners often do not have adequate cognitive structures for accommodating new concepts. In these cases, designing activities that prepare students for future learning can be an efficient

strategy, and the PFL framework is based on this assumption [5]. In other words, this approach encourages students to generate their own ideas about a class of phenomena. Previous work [5], [34], [35] suggests that this preparation sets the stage for future learning; once students develop their own personalized theory about a phenomenon, they can contrast their own thinking with that of others, including experts. In the following paragraphs, we describe how a PFL approach coupled with a tangible user interface has the potential to help students develop a deeper understanding of a concept.

First, a beginner's perception of a situation is not as discerning as that of experts. Experts can often distinguish similar cases by observing small differences, whereas novices categorize them as identical. One example given by Bransford and Schwartz [5] is the case of a tailor who is able to distinguish between dozens of scissors and precisely describe in which situations each one should be used. People lacking that kind of expertise would just label them as "scissors" and miss the subtle differences that make them tailored to a specific problem. Bransford and Schwartz argue that students who analyze contrasting cases can cultivate their perceptual skills to develop an understanding of the deep structure of a problem (as opposed to superficial observations based on surface features). This training, in turn, helps students develop a deeper understanding of a concept when listening to a lecture or reading a textbook chapter. Contrasting cases originally came from Gibson's work [12] in perceptual psychology; these cases are instructional materials that reflect the same phenomena (or objects), with small variations. Some of those variations may be surface features, while others may reflect profound changes in deep structure. The following studies illustrate two applications of the PFL framework in which students took advantage of a set of contrasting cases.

In one study, Schwartz and Martin [34] demonstrated that novices in statistics who developed a variance formula for a set of contrasting cases were better able to transfer this concept to a subsequent example than were students who experienced tell-and-practice instruction. In this learning activity, the students had to invent a reliability index for baseball pitching machines; four contrasting cases described the performance of each machine. Students who were able to invent a measure that replicated the concept of the standard deviation identified the deep structure of the problem and were, thus, able to take full advantage of the subsequent lecture. In another study, Schwartz et al. [35] replicated the same results by teaching the concept of the ratio to eighth graders; in the treatment group, students had to invent a "crowdedness index" for different companies of buses transporting clowns. A learning test showed that the children who followed a PFL activity outperformed the students who experienced "tell-and-practice" instruction. In both studies, learning gains were measured using transfer problems: Transfer problems typically lack small clues that indicate which formula students need to use to answer the question. Thus, only the students who perceived the deep structure of the problem were able to correctly address those transfer questions.

In summary, the PFL framework postulates that contrasting cases help students separate the surface features from the deep structure of a problem; this, in turn, prepares them for future learning. More generally, contrasting cases

provide an opportunity for students to develop their own theory of a phenomenon: While working on those cases, students can formulate assumptions, develop hypotheses, confront ideas, and make their preconceptions explicit.

Within the PFL framework, we believe that Tangible User Interfaces (TUIs) can offer special affordances for exploring a problem space. First, TUIs are known as being less constrained and more engaging than standard interfaces [27]. They also support and incentivize students to explore a wider portion of the problem space. In certain contexts, a higher level of exploration of a learning environment has been associated with positive learning outcomes [31]. Second, we propose that actively manipulating objects supports students' elaborations of a phenomenon. In cognitive psychology, the elaboration effect is known to be beneficial to knowledge acquisition [39]. We believe that text-based environments offer fewer opportunities for elaborative processing because the verbal channel is already working on written material or listening to a professor [23]. A core idea of the PFL framework is to support students' construction of their own theories [5]; by supporting students' elaborations and explorations, TUIs may leverage the PFL approach in an interesting way because participants' explorations and elaborations can be augmented by tangible and digital information.

2.2.2 Implications for Learning

In the field of neuroscience, given its complexity and dynamicity, we believe that students may be missing rich learning opportunities by passively attending lectures and using printed, static learning materials. This is especially true in fields in which the content is not a linear progression of topics but an interconnected web of concepts. As previously described, the PFL framework has interesting implications for improving the learning of dynamic systems such as the brain. TUIs are interesting learning environments because, due to their flexibility and to the unique combinations of media that they afford, they have the potential to increase engagement [32], support students' exploration of a problem space [31], increase the quality of collaboration in small groups [36], and facilitate access to complex learning materials [20]. We will come back to those points below (Section 2.3).

2.2.3 Hypotheses

Based on the PFL framework, we propose that having students generate their own thoughts about a problem will better prepare them for learning from a subsequent textbook or lecture. Additionally, we propose that, in the field of neuroscience, a tangible environment provides specific affordances that prepare students for future learning (i.e., by having them develop their own theory of a phenomenon). This will help students develop a deeper understanding of the domain taught when reading a text or listening to a lecture. In comparison, based on the PFL framework, we predict that starting from an abstract representational system, such as a text, offers fewer opportunities for anchoring new knowledge when studying a domain. This position is in line with constructivist theories of learning [25]. However, it may be that students who read a text first will outperform the ones who start with a hands-on activity. This position is supported by traditional instructional models used in most classrooms

(especially in STEM disciplines—sciences, technology, engineering, and mathematics): Students are first presented with a description of a topic (either via a lecture or a textbook) and then instructed to practice what they have learned with exercises. The "tell-and-practice" approach is widely used because it is a convenient and efficient way to deliver knowledge. The goal of this experiment is to contrast these two instructional views in a complex and novel domain such as neuroscience. The second contribution of this study is to apply the PFL framework to an educational TUI.

More specifically, we used a TUI within the PFL framework and contrasted it with standard instruction by comparing two experimental conditions:

- "Table→Text" ("PFL" treatment group): Students first explore the problem space by generating hypotheses with a tangible interface. The students then study a text on the same topic to compare their understanding of those concepts with this standard learning device.
- "Text→Table" ("tell-and-practice" control group): Students first read a text describing the concepts of interest and then assess their understanding of those concepts using a tangible interface.

We acknowledge that BrainExplorer does not perfectly follow the PFL guidelines. In typical PFL instruction, students work on a limited set of contrasting cases (approximately four) and compare different models side by side to extract their deep structures. In our case, students generate their own contrasting cases, which makes our system more open ended than a traditional PFL activity. However, we believe that our system operates under the principles described by the PFL framework: The key is to help students generate hypotheses before experiencing a more standard type of instruction (e.g., lecture, textbook). More specifically, our participants created multiple lesions on a factice brain while our system displayed the consequences of their actions on the brain's visual field. We consider each lesion to be a distinct case that students had to compare to other lesions; this unordered set of "on-demand" contrasting cases provided the same functionality described [34], [35] in the PFL framework.

2.3 Related Work: Tabletops and Tangible Interfaces for Education

Over the last decade, a significant number of tabletops have been created for educational settings [11], [13], [14], [15], [24], [27], [29], [31], [32], [36], [41]. Researchers believe that tabletops offer unique affordances for designing hands-on learning activities [20]. We review here their empirical results and categorize those projects according to the interactive opportunities they provide.

First, several tabletops use a TUI. TUIs are physical objects that provide information about their state—such as their location—to a computer. The computer senses an event and modifies its output. For instance, when using the Tinker Table environment [45], users can modify the layout of a small-scale warehouse and observe how their actions impact the efficiency of the system. Schneider et al. [31] conducted an evaluation of this tabletop and showed that tangibles better supported the exploration of the problem space, made the task more playful, fostered

collaboration, and helped users achieve higher learning gains compared to those using a multitouch interface. In the field of molecular biology, Gillet et al. [13] augmented physical molecular models with a virtual overlay: The user could change the representation of the digital layer or create new combinations of molecules. Falcão and Price [11] explored the role of interferences in a tangible environment that simulated the behavior of light and showed that conflicts created by shared artifacts supported knowledge-building among children. For physics education, Tseng et al. [41] developed a vertical surface for children to design and explore complex systems made of gears, pulleys, and other mechanical components. For geography education, Ishii et al. [15] created a landscape made of sand that users could freely manipulate; in addition, an augmented reality component provided various simulations illustrating, for instance, the influence of water flows or solar radiation on the geographical layout. In another project, Patten and Ishii [24] used mechanical constraints to create physical affordances: The task of the users was to place cellular telephone towers on a horizontal surface and use wooden accessories as a way to support their natural understanding of the system.

In summary, the projects mentioned above take advantage of several properties of tangibles: They enable an *enactive* mode of reasoning [6] by adding sensorimotor information to the learning process. TUIs also have the potential to provide more compelling and dynamic representations than traditional paper schemas by adding a digital layer to the learning material [13], [15], [45]. In addition, combining physical and digital information facilitates the display of Multiple External Representations (MER; [1]). MERs are believed to support learning by encouraging the use of multiple strategies, offering several viewpoints of a problem, and taking advantage of users' familiarity with one representation to help them transition toward more complicated representations. Finally, physical objects foster collaboration by facilitating the establishment of joint visual attention and associated verbal interactions [11].

Second, several projects have focused on multitouch surfaces to provide natural ways to interact with a system. In genomics, Shaer et al. [36] designed *G-nome Surfer*, a tabletop interface for supporting inquiry-based learning of genomics; their results showed that, compared to a multi-mouse implementation of the system, the multitouch interface increased participation, encouraged reflection, promoted a better collaboration, and provided more natural interactions. Rick et al. [29] conducted a study with children whose task was to organize a classroom with a multitouch interface and showed that territoriality played an important role when users had to collaboratively solve a task in this way. In the same study, Harris et al. [14] compared a single-touch and multitouch surface and described how children doing a planning task focused their discussion on turn taking with the former interface and talked more about the task with the later one. Finally, for medical rehabilitation, Dunn et al. [9] tilted a Microsoft Surface and showed how multitouch games can be used to help children with cerebral palsy practice desired exercises.

This exploratory work suggests that TUIs and, more generally, tabletops support the exploration of a problem space [31], foster balanced interactions between users [30],

provide accessibility to complex learning material [20], promote embodied learning [27], [41], and assist the establishment of joint attention [11] as well as other collaborative processes [32].

3 BRAINEXPLORER

3.1 Design Guidelines

The first phase of the research was a series of semiclinical interviews with six students, in which we sought to further evaluate the shortcomings of neuroscience education reported in the literature. Those interviews were semi-structured and informed us about the current limits of textbooks and classroom instruction. We asked students to describe their experience studying neuroscience, to list topics that were well taught or poorly taught, and to explain why they thought some concepts were difficult to understand. The interviewer took notes during the interviews; we then reorganized those notes into groups to discern the following weaknesses in traditional neuroscience education:

- *Representational problem*. Two-dimensional pictures are inadequate for forming a mental image of complex three-dimensional structures.
- *Wrong focus of attention*. Two-dimensional images emphasize brain regions, whereas the connections between those areas are much more important.
- *Terminology*. A special vocabulary is required to read textbooks. This language barrier makes it difficult for novices to comprehend the topic.
- *Detached from reality*. Most learning activities are grounded in schemas and readings. Most students have difficulty in studying content based solely on abstract material.

Our design of BrainExplorer sought to overcome the issues that surfaced in these interviews in addition to those that our literature review indicated. We aimed to create an engaging, hands-on activity meeting the following requirements:

- *Real-world material*. Our system should allow the user to observe and manipulate a to-scale replica of the brain, allowing them to anchor their knowledge in a more familiar representation and decreasing the cognitive load of manipulating a complex mental model.
- *Improved focus of attention*. Our interface should naturally and dynamically guide users' attention to what matters the most (in our case, the connections between the different brain parts and the flux of information among them).
- *Easy access for novices*. The affordances of the system should allow beginners to interact in a meaningful way with our system ("low threshold,") even before acquiring the specialized terminology. There should not be any prerequisites for exploring how the human brain works.
- *Grounded in sensorimotor actions*. It is important to provide an active learning experience to our users that promotes the discovery of neuroscience concepts.
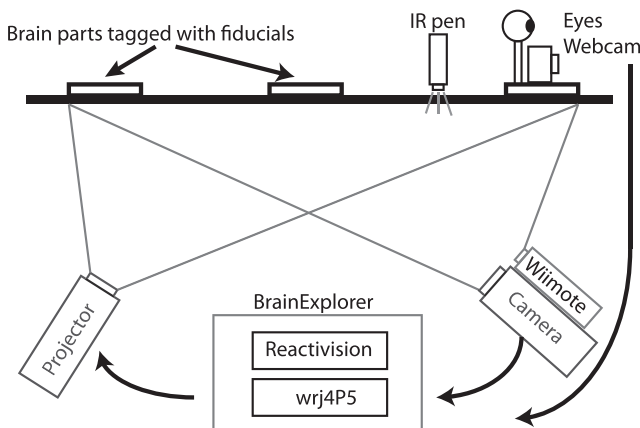
Fig. 2. The setup of BrainExplorer.

Fig. 3. A top-down view of BrainExplorer. The outer left optical radiation is cut (1), which means that the top right corner of the visual field (2) is not perceived by the brain.

- *Rich exploratory paths.* The system should be structured as a microworld in which multiple discovery paths are allowed and many different inquiry outcomes are possible, rather than as a rigorously scripted environment.
- *Low cost.* One significant requirement is designing an inexpensive system that can be replicated to provide multiple learning environments for a single classroom. The system can be extended to or even reprogrammed for other content topics with similar requirements.

In summary, we built our system to address the shortcomings of the predominant educational model and learning materials in neuroscience. Our goal is to improve the learning experience of students by leveraging those preliminary findings. We chose neuroscience as an example of a new field of knowledge that challenges traditional teaching techniques. Our larger research agenda is to show that, ultimately, many similar fields that involve dynamic, three-dimensional, interconnected, complex systems (i.e., molecular biology, nanotechnology) could also benefit from applying the PFL framework to TUIs. We believe that the teaching of this type of content will become increasingly widespread as scientists make new discoveries and push the boundaries of science. On a larger scale, our work can provide some foundations for how to best teach these complex domains.

3.2   Learning Objectives

Our goal is for students to learn about the structures involved in processing visual stimuli, their spatial locations in the three-dimensional brain, how information is processed in the visual system, and what effects specifically localized lesions might have on a person's visual field. We chose these learning objectives because they are appropriate for novices while not being completely trivial. The visual system is usually taught to incoming students in psychology and neuroscience and, thus, is a perfect introductory domain for our system.

3.3   Audience and Setting

Our system is targeted to a wide range of educational settings. The primary purpose of this tool is to promote inquiry-based learning for college students by engaging them in a scaffolded investigation of the brain. Because laboratory research with hands-on experiments using real brains is not logistically feasible in most schools, our system could provide an enhanced learning experience. More advanced prototypes using the same underlying technology could be used by researchers in neuroscience to teach even more advanced concepts at the university level.
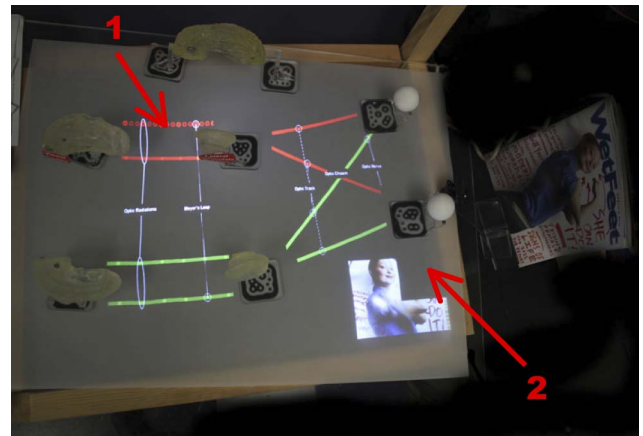
3.4   Hardware

We built a custom tabletop upon which a polymer-based replica of the brain can be deconstructed, manipulated, and reconstructed (Fig. 2). The locations of the brain's parts are tracked with a high-frame-rate webcam underneath the table.

We used the Reactivision framework [18] to tag and detect the different brain regions. An additional camera is placed between the eyes and records what the brain would perceive. Moreover, a short throw projector displays the brain's connections from underneath the tabletop. A quarter of an inch thick acrylic sheet with a sheet of velum on the top provides a semitransparent surface for supporting the tangibles and displaying the layer of augmented reality. Finally, users interact with the connections by *severing* them; this is accomplished by using an infrared pen whose signal is detected by a Wiimote. Fig. 2 describes the hardware components of BrainExplorer.

3.5   Software Architecture

The software behind BrainExplorer is written in Java (more specifically, Processing [28]). We took advantage of existing libraries such as the Reactivision framework for fiducial tracking [18], the wrj4P5 for interpreting the infrared signal detected by the Wiimote and various open-source libraries for displaying and modifying the webcam input from the eyes (Fig. 3). The system is modular and can easily accommodate the creation of additional pathways or learning scenarios.

4   EXPERIMENT

4.1   Participants

There were 28 participants (13 males, 15 females; average age $= 28.2$, SD $= 5.7$) who took part in this study. The sample was randomly selected among graduate students
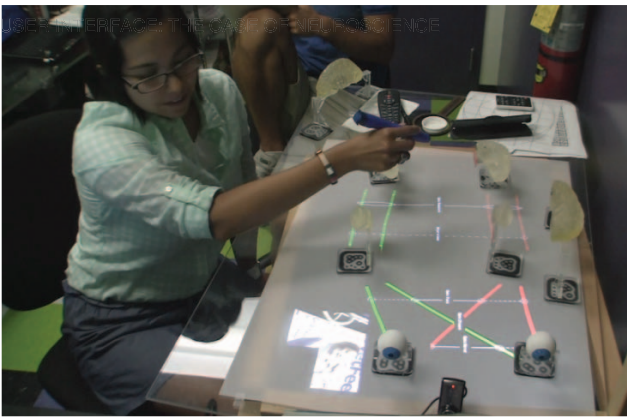
Fig. 4. A user has cut the left inner optical radiation and is reflecting on the impact of the lesion. On the bottom of the picture we can see that the right corner of the visual field is impaired—the system shows the user what the brain would "see" as a result of the connections that were cut.

Fig. 5. The design of our evaluation. One group used the tabletop environment first and then studied a text, while the other group did the same activities in reverse. Each phase was preceded and followed by a test.

who were present on campus during the time of the study. To make sure that none of them had prior knowledge of neuroscience, we presented them with a diagram of the human brain before the experiment. We asked the participants to describe the visual pathways present on the drawing and predict how different lesions would impact the visual field of the brain. The participants in our study either declined to answer because they did not know the solution or made one or several wrong guesses. All of them confirmed that they never took a neuroscience class in the past.

4.2 Material

In one condition ("table → text"), users explored the brain's visual system using the system previously described. In the other condition ("text → table"), users read an abridged version of an introductory text on the same topic. We modified the materials in this condition to provide the same amount of information for both groups[2]: A final section providing additional information about the anatomy of the brain was removed because the tangible interface did not display those regions.

The tests used in this study were identical in both conditions. The pretest was conducted informally: The experimenter showed a diagram of the visual system to the participants and asked them if they could identify any brain parts or connections and whether they could predict the effects of different lesions on the visual field. Participants qualified for the study if they could not provide any correct answers. The interim test was computer based: Participants followed instructions on the screen and answered three types of questions: *Terminology* (identify a brain part or brain connection), *effect of a lesion* (choose an impaired visual field from multiple answer options that would result from a brain lesion), and *transfer* (offer an opinion on a medical case and a neuroscience research project based on what was learned). The whole test included seven terminology questions, seven questions about lesions and three transfer questions. The posttest was similar to the interim test except that the side of the brain was reversed: If a
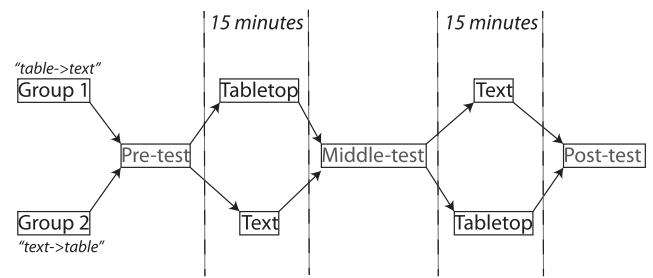
question was related to the right side of the brain in the interim test, the same question would pertain to the left side of the brain in the posttest. All questions were counterbalanced across the interim test and posttest.

4.3 Design

We used an AB/BA cross-over design in this study (Fig. 5). One group first took a pretest, went through treatment A (using the tabletop for 15 minutes), completed an interim test, received treatment B (reading a text for 15 minutes) and finally took a posttest (this group is labeled "Table → Text"). The second group completed the same sequence except that they began with reading a text and then used the tangible interface (labeled "Text → Table").

Because the goal of treatments A and B was to teach the same content, we cannot compare the within-subject effects between the interim test and the posttest. However, the between-subject differences on the interim test provides us with a direct comparison of the textbook and tabletop effects on learning. Moreover, the posttest describes the effect of the sequences on the final learning gains. In other words, is A-B more efficient than B-A?

4.4 Coding

Students' answers to the pretest, interim test, and posttest were evaluated as correct or incorrect. Scores were automatically computed at the end of each test. We videotaped each session and coded them according to the number of lesions generated and their locations. We also asked the participants to think aloud during the tabletop activity and categorized every utterance they produced according to the coding scheme described in Table 1.

4.5 Procedure

Participants were run individually in a private room. Upon arrival, the experimenter welcomed the participants and thanked them for their participation. The participants were then presented a schema of the brain highlighting the visual pathways and asked to identify seven brain parts and connections as well as to predict the effects of seven specific lesions on the visual field (Fig. 4).

After completion of the pretest, half of the participants studied a text describing how visual information is processed in the human brain. The other half of the participants were introduced to the BrainExplorer environment and given a brief explanation of how to interact with the system. They also received the following instructions: "Your goal for this activity is to explore how the visual system of the human brain works. While you interact with

2. The text used can be accessed at http://www.scribd.com/doc/ 98921800. Originally retrieved from Washington University in St-Louis (http://thalamus.wustl.edu/).

TABLE 1
Coding Scheme for Participants' Utterances

CATEGORY	EXAMPLE
(1) Simple observation	"I cut Meyer's loop on the right side of the brain, and the upper left corner of the visual field is impaired."
(2) Prediction	"If I cut the optic chiasm, I expected the periphery of the visual field to be lost."
(3) Confrontation between a prediction and a result	"I was expecting the visual field to be somehow impaired by cutting the outer optic nerve of the right eye, but nothing happened."
(4) Definition of a rule or principle	"The brain seems to divide the information between right and left visual field before the LGN, and between bottom and top vision right before the visual cortex."

All the participants' utterances were coded according to the coding scheme above. This coding scheme was applied only to the "tabletop" session for each group.

this system, try to define two rules that will help you explain to someone else how visual information is processed in our brains. Those rules need to summarize your findings during this activity." Participants were also asked to think aloud and describe how they interacted with the system. This task was afforded 15 minutes in both conditions. Participants then completed a computerized interim test to assess their learning gains. Upon finishing the test, the participants went through the "text" activity if they had previously used the tabletop and vice versa. Finally, they completed a posttest and were thanked for their participation. The experimenter also asked the participants a few questions, e.g., did they feel like the tabletop environment helped them learn how the visual pathways of the human brain work? and how did the two activities help them understand those concepts? The whole activity took between 60 and 80 minutes for each participant. The experimenter then debriefed the participants and explained to them the goal of the study.

4.6 Rationale for Comparing BrainExplorer with a Textbook Chapter

The goal of this study is to improve the way neuroscience is taught. More specifically, we suggest that current education in neuroscience relies on complicated two-dimensional representations and a linear explanatory model that places a high cognitive load on students and miss the opportunity to explore different representations that are now possible with new technologies. Novices spend a significant amount of energy reconstructing and manipulating complex mental models without the support they need, while they should be focusing on understanding the dynamic, interconnected nature of the brain as a complex system. Our ecological evaluation provides insights on 1) how technological systems can improve classroom instruction and 2) how

learning environments can be integrated with traditional learning materials (e.g., textbooks). Our study, however, does not attempt to explain why one instructional method is more efficient than the other; future studies should focus on those differences and highlight the strengths and weaknesses of each method. More specifically, we contrasted the two following models: 1) a constructivist approach in which students were given the opportunity to first develop their own explanations of a phenomenon with a hands-on activity and then to check their understanding with a text, and 2) a classical approach (used in current classrooms) in which students were first exposed to formal theories and then practiced their understanding of those concepts with hands-on problems.

4.7 Hypotheses

Our work is based on the assumptions that 1) current education in neuroscience is using unnecessarily complicated representations without the correct scaffolding and preparation, and 2) for highly dynamic and complex content, students who participate in a hands-on activity in which they can generate some prior knowledge before reading a text will outperform students following a standard "tell-and-practice" procedure. As a result, the two following hypotheses guided our evaluation:

- *H1.* Students will better learn neuroscience concepts using a tabletop employing a tangible interface that encourages prior knowledge building compared to using a traditional textbook.
- *H2.* Students who learn first with an engaging, hands-on activity in which they can create their own contrasting cases and then study a textbook chapter will outperform students who read a text and then complete the hands-on activity.

5 RESULTS

5.1 Learning Gain (Hypothesis 1 and 2)

To evaluate the results, we computed students' scores on each learning test. The interim test revealed that participants in the Tabletop condition scored significantly higher than those reading the text: $F(1,26) = 15.77$, $p < 0.001$. The posttest also revealed a difference in favor of the group using the tabletop first and then reading the text: $F(1,26) = 10.08$, $p < 0.001$. Fig. 6 summarizes our results. On the interim test, the "Table $\rightarrow$ Text" group outperformed the "Text $\rightarrow$ Table" group on the questions concerning brain terminology ($F(1,26) = 5.18, p < 0.05$) and on the transfer questions ($F(1,26) = 24.98, p < 0.001$) but not on the questions related to the effects of the lesions ($F(1,26) = 1.02$, $p = 0.32$). On the posttest, we found that the "Table $\rightarrow$ Text" group showed higher learning gains on the terminology ($F(1,26) = 6.86$, $p < 0.05$) and the lesions questions ($F(1,26) = 5.80$, $p < 0.05$) but not on the transfer questions ($F(1,26) = 0.84$, $p = 0.37$).

5.2 Comparing Process Variables: Student Exploration of the Problem Space and the Quality of Verbalizations (Posthoc Analysis)

We also analyzed to what extent participants explored the problem space. More specifically, we counted how many lesions they generated when using BrainExplorer. We found
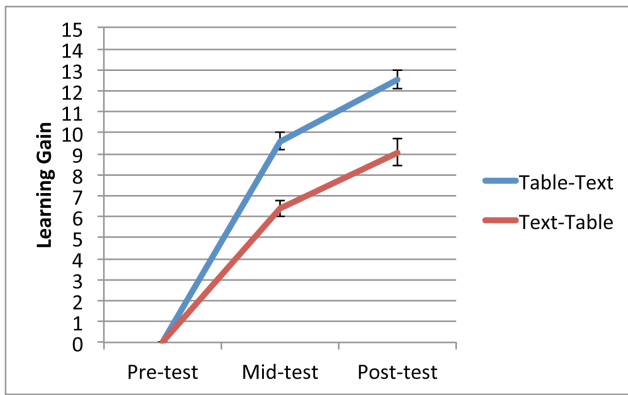
Fig. 6. Learning gain from the interim test and the posttest. Participants in the "Table → Text" condition used BrainExplorer first and then read a text. Participants in the "Text → Table" condition read a text and then used BrainExplorer.

that participants in the "Table → Text" condition cut more connections (mean = 32.15, SD = 11.93) than in the "Text → Table" condition (mean = 28.45, SD = 6.49). This difference, however, was not significant: $F(1,22) = 0.84, p = 0.37$. Interestingly, students in the "Table → Text" condition learned more while making approximately the same number of lesions as the other group. The number of lesions generated was not significantly correlated with participants' learning gains: $r(26) = 0.19, p = 0.37$.

In addition to analyzing test scores, we also analyzed participants' speech during the hands-on activity by coding the video recordings [8]. We classified every utterance produced by the participants according to the coding scheme defined in the Methods section. We had four categories:

1. simple observations,
2. predictions,
3. comparing a prediction with a result, and
4. defining a broader rule that explains how the visual pathways work (this rule has to be applicable to more than one case, otherwise it is categorized as a simple observation).

Fig. 7 summarizes how participants spent their time working on the table in each experimental condition.

In our content analysis, we focused on the quality of the verbalizations produced by the participants when using BrainExplorer. More specifically, we wanted to investigate whether one group took better advantage of the tabletop (Fig. 7). Our results show that participants in the "Table → Text" condition produced significantly more rules explaining how the visual pathways work: $F(1,22) = 8.82, p < 0.01$ (m = 0.22, SD = 0.11 for "Table → Text," m = 0.11, SD = 0.05 for "Text → Table"). We did not find significant results for the number of observations $(F(1,22) = 2.80, p = 0.109)$, predictions $(F(1,22) = 2.43, p = 0.133)$, and confrontations $(F(1,22) = 0.44, p = 0.51)$ that participants made. There was not a significant difference in the total number of utterances between conditions: $F(1,22) = 0.39, p = 0.54$. Finally, we found that the number of rules produced was positively correlated with participants' learning gains: $r(26) = 0.58, p < 0.01$.
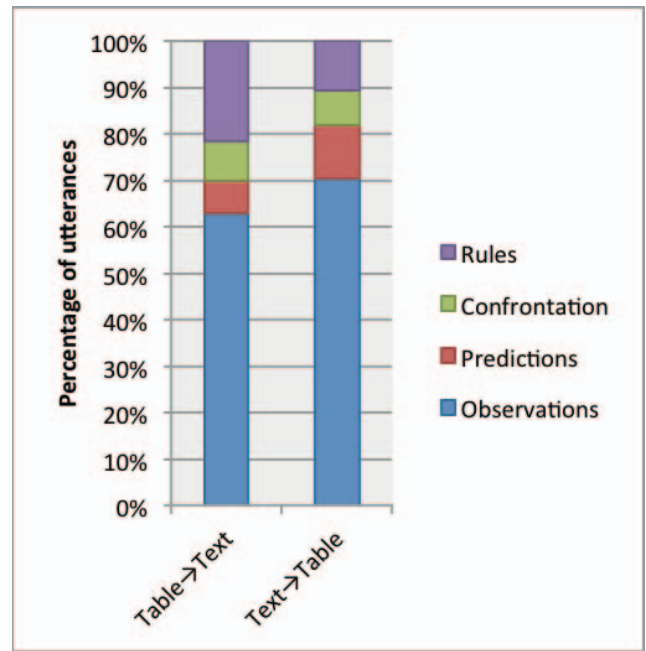
Fig. 7. Content analysis of the participants' utterances. We coded the think-aloud sessions according to the coding scheme defined in the Methods section (making a simple observation, predicting a result, confronting a prediction, and defining a rule based on a set of observations).

5.3 Contrasting Our Process Variables with a Mediation Analysis

To further investigate the differences between students' explorations and elaborations while using BrainExplorer, we conducted a mediation analysis with the two following "mediators:" the quantity of connections cut (i.e., to what extent our participants explored the problem space) and the quality of their verbalizations (i.e., to what extent they elaborated on the content while making lesions). A mediation model assumes the existence of one or several variables (called "mediators") between the dependent (DV) and independent measures (IV). A meditational model assumes that the IV causes the mediator variable, which in turns causes the DV. We tested for multiple mediations using Preacher and Hayes' bootstrapping methodology for indirect effects [26]. Our approach uses 5,000 bootstrapped resamples to describe the confidence intervals of the indirect effects in a manner that makes no assumptions about the distribution of the indirect effects. The bootstrap data are interpreted by determining whether zero is contained within the 95 percent CIs (thus indicating a lack of significance). The results for multiple mediations showed that only the number of "rules" created by our participants (CI: [0.29; 4.89]) was a significant mediator of positive learning gains (Fig. 8). Exploration was not found to be a significant mediator (CI: [−0.47,1.47]).

5.4 Field Notes and Semiclinical Debriefing Sessions

As described in Section 4.5, we collected two types of qualitative data. First, the experimenter took field notes while observing the participant's interactions with the table. Second, we conducted a short debriefing session with each participant at the end of the experiment (between 5 and
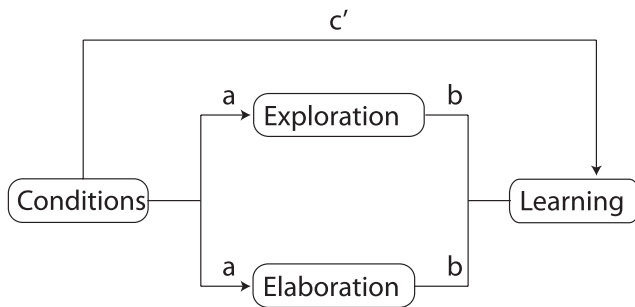
Fig. 8. We conducted a mediation analysis to determine whether the quality of students' elaborations and the number of connections cut were significant mediators of a positive learning gain. Only the quality of their verbalizations was found to be significant.

10 minutes). We asked them how they thought the two activities related to each other and how they would improve upon the entire learning activity. Although those observations were not quantitatively analyzed, they provided interesting insights into our users.

If we consider only the interim test, the users in the "Table → Text" group often did not try to generate all the lesions that are possible when using BrainExplorer. However, they still learned the material better than the participants in the "Text → Table" condition. This suggests that even though the first set of participants did not access all of the material, they better learned the subset of the content that they did explore. Participants in the "Text → Table" condition were exposed to a clear description of all the material for the first test; however, they did not score higher on the learning test than the other group.

In addition, the debriefing sessions revealed that users in the "Table → Text" group felt that studying the text after using the table was beneficial to their learning experience. However, more than half of them believed that reading the text before exploring the topic with BrainExplorer would have helped them to better understand the material. Joe, for instance, mentioned, "I would have been better able to take full advantage of the table if I had read the text beforehand." This comment is interesting because it directly contradicts our findings. It also suggests that students are not the best judges in regard to defining ideal learning situations. The implications of our results are discussed below.

6 DISCUSSION

In this study, we investigated 1) whether a tangible, constructivist, microworld-based learning environment is better suited for learning about neuroscience than a text version of the same content, and 2) if the sequence of activities influenced the way participants learned. We tested those two hypotheses using an AB-BA cross-over design. Our results suggest that participants not only learned more with BrainExplorer but also that they benefit more from the table if they use it before reading a text on the same topic. These results have several implications for the design of educational tangibles and learning activities related to neuroscience and possibly other topics.

Specifically, our findings provide preliminary evidence that BrainExplorer better supports knowledge building than a traditional text version of the same learning material.

Future studies should isolate which components of Brain-Explorer explain most of the variance in this outcome: Did our system outperform the text activity because users were able to explore the domain at their own pace or because the three-dimensional physical representation is more appropriate for learning concepts related to the spatial nature of the brain's functional systems? Additionally, participants in the two conditions were given slightly different instructions. For the tabletop activity, the experimenter asked the participants to define two rules summarizing how visual information is processed into the human brain. For the text activity, he asked them to learn as much information as they could from the text. It is important to mention that those two rules were clearly defined in the text, which made the previous instructions superfluous. Thus, which of the three confounding variables caused the positive learning gain we observed? Answering this question was not a goal of this paper, but it is definitely in our research agenda. As previously mentioned, our goal was to conduct an ecological comparison of direct instruction and a hands-on activity in which students built their knowledge in a personalized way. We argue that the type of instructions we gave to each group were inherent to those approaches. It is the role of subsequent studies to disentangle the effects of those variables on the learning outcomes.

More importantly, we found that properly sequencing learning activities when using a tangible interface is crucial for knowledge building. Participants in both conditions used identical materials for learning; the only difference was that they completed the two activities in a reverse order. The participants who used BrainExplorer first and then read the text significantly outperformed the group who read the text first. This result indicates that learning activities do not have additive effects; they are not interchangeable. On the contrary, learning activities interact in complex ways. Our results suggest that the participants who used BrainExplorer first took better advantage of the learning opportunity offered by the textbook chapter. This view is supported by a constructivist view of learning [25], by research on the use of microworlds in science and mathematics instruction [10], and more specifically by the PFL framework [5] under which inventions or discoveries made by students better prepare them for future learning. Again, there is one important limitation to our results: The students did not receive the same instructions when starting the experiment. The participants in the "table → text" condition were asked to summarize their hypotheses aloud while exploring the tangible environment. Participants in the "text → table" condition were asked to simply study a text. This difference may have caused the effects found in the posttests. We discuss the influence of this confounding variable in the "limitations" section below.

We tried to explain these differences by contrasting two of the posthoc measures: First, we hypothesized that students' explorations of the problem space would predict their scores on the final learning test (a "quantity" hypothesis). This view is supported by previous work showing that users tend to "try" more solutions with physical manipulables, and that exploring a problem space is associated with a positive learning gain in some contexts [31]. Second, we hypothesized that the quality of students' verbalizations would also predict their scores on the final learning test (a "quality" hypothesis). Higher quality

elaboration is usually considered beneficial for learning [38]. We did not have any strong hypotheses concerning these posthoc measures because both processes can be beneficial to learning (i.e., exploration and elaboration). Our goal is mainly to provide a general trend describing the effect of traditional instruction on a theory-building activity conducted on a tangible interface. Our analysis disconfirmed the quantity hypothesis and confirmed the quality hypothesis. We did not find any significant differences in the students' degree of exploration of the problem space across our two conditions. In other words, they cut the same number of brain connections, showing that exploration per se is not always associated with positive learning outcomes. This result suggests that simply looking at the extent to which students explore a situation can be misleading if taken by itself. Our results also show that reading a text before using BrainExplorer reduces how much users explore higher level concepts compared to using a TUI first. Indeed, the participants who were exposed to the content taught on the tabletop first produced more "rules" (i.e., general principles that apply to more than one situation) than the "Text → Table" group; we interpret this result as an attempt from the participants to isolate patterns associated with the dynamic nature of the brain. From a constructivist perspective, they were interactively seeking to make sense of the physical situation available to them in the exploratory TUI condition by trying out a variety of intuitive moves to infer patterns of relationships. By contrast, we hypothesize that the users who read the text beforehand felt that they had already been exposed to the underlying concepts and, thus, entered the second activity with nothing left to "discover." However, as the posttests show, their sense of having learned the material was not accurate. This finding might have important implications for instruction. For example, students reading a text might erroneously feel that they have mastered the material and do not need to put much effort into subsequent exploratory or lab activities, but our data show that they will more quickly forget what they have learned in this case. Additionally, these results are confirmed by the mediation analysis we conducted: We found that student elaboration (measured by the number of "rules" they produced) was a significant mediator of positive learning gain. However, student exploration of the problem space was not a significant mediator of learning. These results contradict those of Schneider et al.'s study [31]. Future work is needed to determine in which situations exploration plays a significant role in student learning.

As a side note, our postexperiment interviews led to an interesting finding. Most users who used the tabletop first suggested that they would have benefited more from the system if they had read the text beforehand. However, our data directly contradict their expectations. It seems that the participants from our sample were not the best judges of what would assure the most effective learning experience. This observation should be kept in mind when designing learning environment and gathering informal feedback. We hypothesize that users tend to spend their energy in a very economical way; reading a text is an easy way to access information and, thus, leads students to believe that they have "saved energy." Additionally, the discovery activity is less predictable and familiar than reading a text, and students are left without knowing the right answers to the activities for some time. Students might translate this

immediate discomfort into a desire to use safer resources such as a text. As a consequence, educational designers can be misled by using focus groups and user feedback to guide their learning designs. Users may unconsciously choose a more economic and familiar but inefficient way to learn when given the choice. Additionally, they might not have the metacognitive skills necessary for evaluating whether they have actually learned the material.

In conclusion, the main contribution of our work is the application of a promising educational framework to a relatively new type of interface (TUI) in a novel content area. We chose neuroscience in particular because it represents a challenging type of content that is increasingly prevalent in college courses. To our knowledge, this is the first attempt at designing an interactive tabletop environment specifically for the PFL framework. We argue that tabletops are legitimate exploratory, microworld-like learning environments, and that they can satisfy the constraints of a PFL activity. Obviously, our results do not indicate that TUIs are a panacea for all disciplines; however, they show that the TUI and PFL combination may work particularly well for certain learning contexts. Among these contexts, neuroscience seems to be an ideal candidate for the hands-on activities associated with TUIs. Future work should investigate related disciplines (e.g., with dynamic, three-dimensional complex systems) and examine whether tangible environments bring similar learning benefits.

One implication for design is that, at least for this type of content, and under the assumption that our participants were using the textual resources as efficiently as such resources can be used, offering students alternative representations and exploratory environments not only is better than a textbook but also constitutes good preparation for future learning. A second implication is that designers should carefully consider the order of learning activities when introducing new learning technologies because the impact of these technologies could be greatly improved by the combination of traditional and new media.

7 FUTURE WORK

7.1 Design

As a pilot platform, BrainExplorer is not ready to be deployed in classrooms. It is part of a larger project of creating educational toolkits that teachers can easily assemble and run in classrooms with compiled binaries and low-cost hardware. Thus, our next step is to make building instructions and the software components of BrainExplorer available online. This will allow interested teachers and early adopters to build learning environments at a lesser cost than commercially available solutions and small businesses to manufacture small batches for schools. This dissemination strategy has worked with several open-source hardware projects in recent years, such as Arduino (a physical computing platform), the GoGo Board (a robotics platform [37]), and the Lilypad (an e-textiles board [7]). These platforms are quickly multiplying in schools, either through early adopter teachers who are able to assemble and use the kits or via educational suppliers who deliver assembled open-source kits and curricula for a fraction of the cost of traditional school hardware.

In the future, we plan to take embodied learning to the next level. To help students comprehend the actual effects

of selective vision loss, we envision creating electronic goggles that receive feedback from the system as to which connections were cut on the tabletop and modify the subject's visual field appropriately. This type of apparatus could be used for different levels of perception (color, depth) and for other senses. Such a learning environment would make the activity even more engaging by simulating lesions on users' own brains. It is worth investigating whether such embodied feedback would improve learning with its first-person perspective.

7.2 Limitations

Concerning the results of the interim test (i.e., students' learning scores after completing the first activity), future studies should isolate the different variables present between our two conditions, as the paper activity was essentially passive and directly described how the brain works. The tabletop, on the other hand, promoted a more active approach and forced users to discover concepts by themselves. We wanted, indeed, to compare the two approaches as such, but additional user studies should separate those variables and provide a more precise explanation as to why we observed a higher learning gain with BrainExplorer. For instance, we could compare how participants learn from the tabletop environment 1) when they are cutting the connections themselves and 2) when an instructor gives a minilesson using BrainExplorer. This would allow us to isolate the effect of "discovering" a concept on student learning.

Concerning the results of the posttest (i.e., students' learning scores after completing the second activity), future studies should ask students to think aloud and generate rules while reading the text. This could be a limitation of our results: It is possible that the slightly different instructions that we gave to our participants at the beginning of the experiment may have influenced the effects found in the posttests. Even if there was some influence due to the prompts, we believe that the influence would be comparatively small because the task was very familiar to most students—read a text, explore a hands-on environment, answer questions—so it is unlikely that a small change in the prompt would cause students to behave in very different ways. From the field notes and recordings, we also observed that most students had to be reminded that their goal was to generate rules while working on the tabletop. This reminder was usually given a few minutes before the end of the activity. As such, we believe that the students were totally engaged in their exploration and did not need our prompt to generate hypotheses. However, because we do agree that this limitation needs to be addressed, we are currently conducting a series of studies in which we are controlling for this effect. More specifically, we are using a similar experimental design with small collaborative learning groups. Groups of students receive the exact same prompts for each step and, thus, can discuss their understanding of a concept with their peers instead of thinking aloud. These additional studies will allow us to estimate the effect of this limitation on our findings and will potentially replicate the results reported above.

8 CONCLUSION

In this paper, we have presented a tabletop environment, where users can explore how the visual system of the human brain works. Our results suggest that neuroscience education can benefit from tangible interfaces and that correctly sequencing learning activities is crucial for promoting knowledge building. In addition, our design process suggests that learning from educational technology is beneficial when the technology is designed as a function of the target content and built on a strong foundation in relevant learning theories such as the PFL framework. Certain domains, such as highly spatial tasks or the study of dynamic systems, may benefit more from using physical objects with augmented reality than others. Future work should continue to investigate which domains can be supported by physical actions and thoroughly document the mechanisms by which TUIs enhance learning. Although our study has limitations, it is an informative first step in investigating how technology can support student learning about complex systems.

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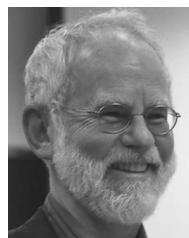
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